Allometric Scaling and Resource Limitations Model of Total Aboveground Biomass in Forest Stands: Site-scale Test of Model

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Abstract: Large-scale mapping of forest biomass uses geospatial predictors such as climate, vegetation indices, soil property, and topography in order to alleviate the discontinuity of *in-situ* measurements in space and time. Here, we present an approach **combining known biophysical processes** and **geospatial predictors** through **parametric optimizations** (inversion of reference measures). **Total aboveground biomass (AGB) in forest stands** is estimated by incorporating the Forest Inventory and Analysis (**FIA**) and Parameter-elevation Regressions on Independent Slopes Model (**PRISM**). Two main premises of this research are: **(a)** The **Allometric Scaling and Resource Limitations (ASRL)** approach can provide a valid relationship between tree geometry and local resource availability; and **(b)** The zeroth order approach (**size-frequency distribution**) can expand individual tree allometry into total AGB at the forest stand level. Two supplementary reference maps from the National Biomass and Carbon Dataset (**NBCD**) and U.S. Forest Service (**USFS**) were implemented to evaluate the model. This research focuses on **a site-scale test of the biomass model** to explore the robustness of predictive power, and to potentially improve models using additional geospatial predictors such as more climatic variables, vegetation indices, soil properties, and lidar-/radar-derived altimetry products (or existing forest canopy height maps).

I. Research Background

⦿ **Large-scale mapping of forest biomass** to quantify forest C sinks/sources.
- Discontinuity of *in-situ* measurements in space & time;
- Use of geospatial predictors such as climate, vegetation index, soil, & topography;

⦿ Recent approaches (e.g., machine learning & spatial statistics) perform well.

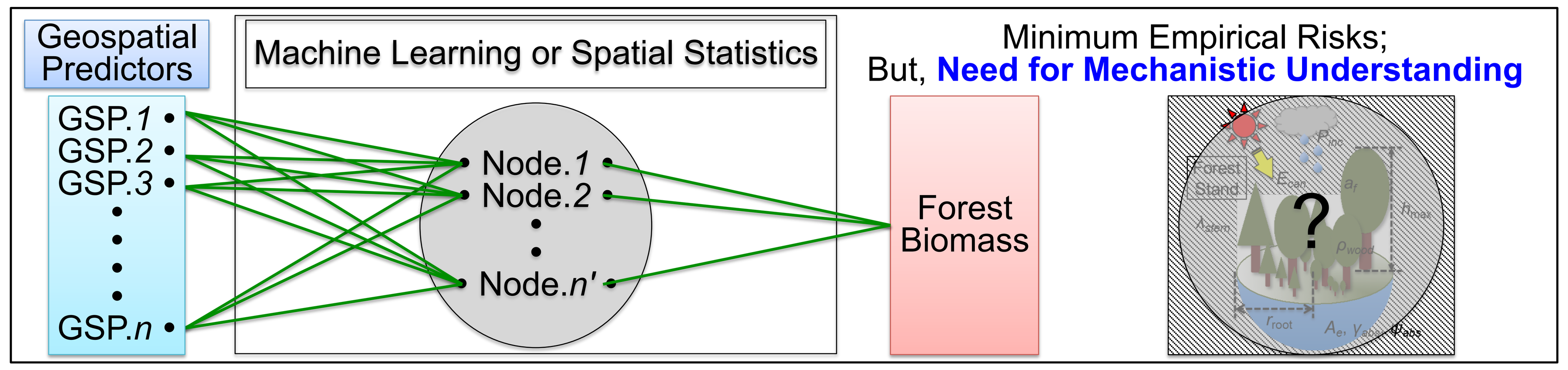


Fig 1. Use of geospatial predictors in recent studies. Being highly predictive with less training errors, but biophysical mechanisms governing forest growth are often neglected.

II. Model Framework

⦿ Total AGB in forest stands (AGB_{TOT})[1] $= \int m(r)\, f(r)\, dr$; here, r = stem radius.
- Individual trees' allometry, $m(r) = c_m^{-1}\, r^{8/3}$, between r & AGB;
- Size-frequency distribution of trees, $f(r) = c_n\, r^{-2}$, with varying size classes;
- Assuming $r_{max} >> r_0$ (smallest tree) in a forest stand, $\boldsymbol{AGB_{TOT} \cong (3/5)\, c_n\, c_m^{-1}\, r_{max}^{5/3}}$;

⦿ **Mechanistic understanding** using the ASRL[2] & zeroth-order[3] approaches.

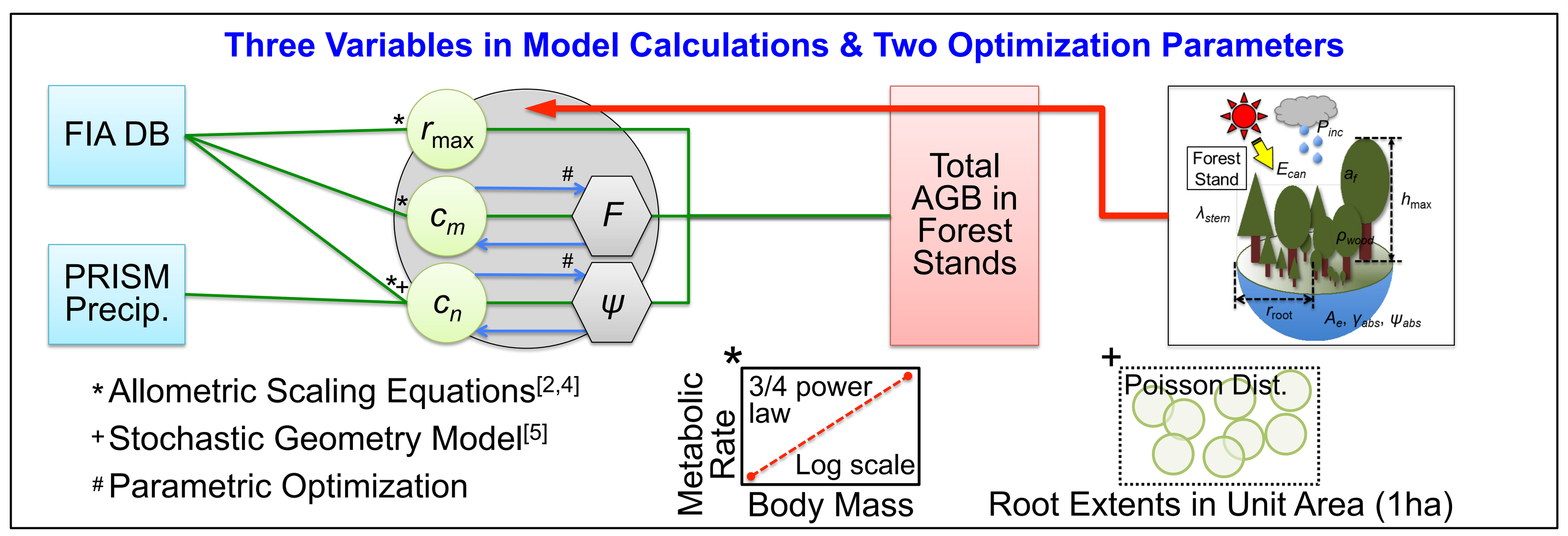


Fig 2. Model driven by stem radius of the largest tree (r_{max}) & two normalization constants (c_m & c_n). Two optimization parameters are tree shape factor (F) & root absorption exponent (ψ).

(1) Norm. const. of allometry, $\boldsymbol{c_m = [10\,(2^{\zeta}\pi)\,\kappa_1\, F\rho]^{-1}}$; (unit: $g^{-1}cm^{8/3}$).

(2) Norm. const. of size-frq. dist., $\boldsymbol{c_n = (4/5)\, Q_{TOT}\,\kappa_2^{-1}\, r_{max}^{-(4/5)}}$; (unit: $cm\ ha^{-1}$).

- κ_1, κ_2, & ζ = empirical scaling for US forests[2]; ρ = wood spec. gravity ($g\,cm^{-3}$);
- Basal metabolic rate (Q_{TOT} in $L\ day^{-1}\ ha^{-1}$) $\leq Q_p = (\gamma P_{inc} A_e)^{\psi}$; here, P_{inc} = incoming precip. ($L\ day^{-1}\ m^{-2}$); A_e = root area ($m^2\ ha^{-1}$), & γ = absorption efficiency ($\approx 1/3$[2]);

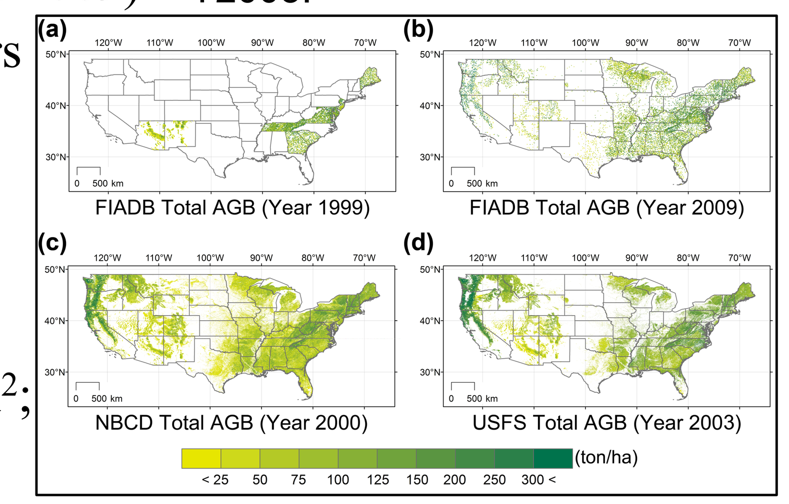
(3) $\boldsymbol{r_{max} = (h_{max}/\kappa_1)^{1/\zeta}/2}$; (unit: cm).
- Based on an allometric scaling rule for tree geometry[2,4];
- **Why h_{max}?** For flexibility to use lidar/radar altimetry data in future studies;

III. Data

⦿ Inputs;
- FIA for allometric info. (inventories in 1999 & 2009)
- PRISM for annual precip. (climatological years 1971–2000 & 1981–2010)

⦿ Evaluations;
- FIA AGB (also for model training/test)
- Two AGB maps from NBCD & USFS
- Eco-regions across scales (subsection, ~25 km^2; section, ~2500 km^2; province, ~25000 km^2)

Fig 3. Reference AGBs. (a,b) FIA AGB Y1999 & Y2009. (c) NBCD AGB Y2000. (d) USFS AGB Y2003.



IV. Optimization & Sensitivity Analysis

⦿ Parametric optimization (F & ψ);
- To minimize training errors against FIA AGB with higher R^2 & Pearson's r, but lower mean-absolute-error (MAE) & RMSE.
- Samples in 12 groups with four tree species types × three annual precip. regimes

⦿ Sensitivity analysis;
- To find empirically realistic extents & intervals of F & ψ (perturbing one, while keeping another).
- $0.03 \leq F \leq 0.08$; $0.95 \leq \psi \leq 1.30$.

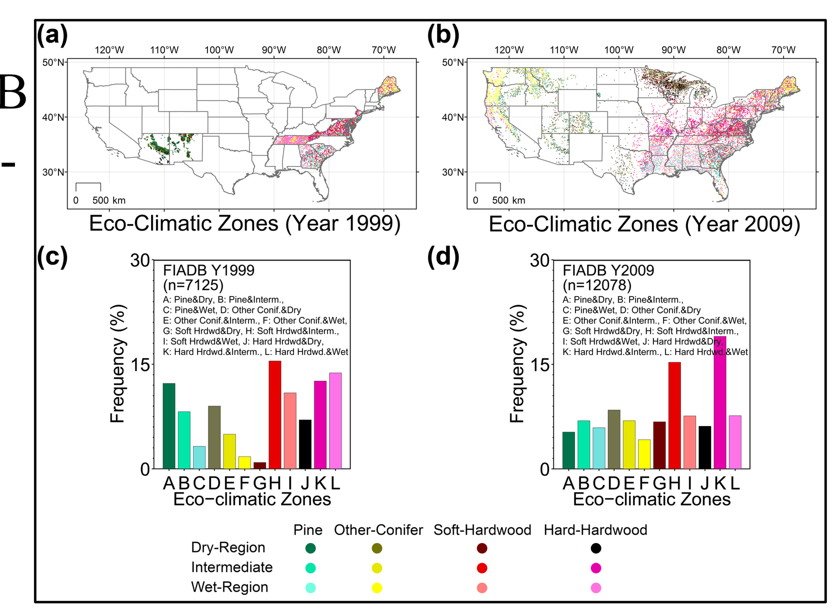


Fig 4. Study sites in 12 zones defined by tree species types & precip. regimes (Dry ≤ 900; Interm.; 1300 mm < Wet).

V. Optimized ASRL Model AGB

- Moderate predictive power: MAE = 43.6; RMSE = 66.5 ton/ha; R^2 = 0.50 (Y2009)
- Stable model performance with the independence between training & test data.
- In general, underestimations in dry regions, while overestimations in wet regions.

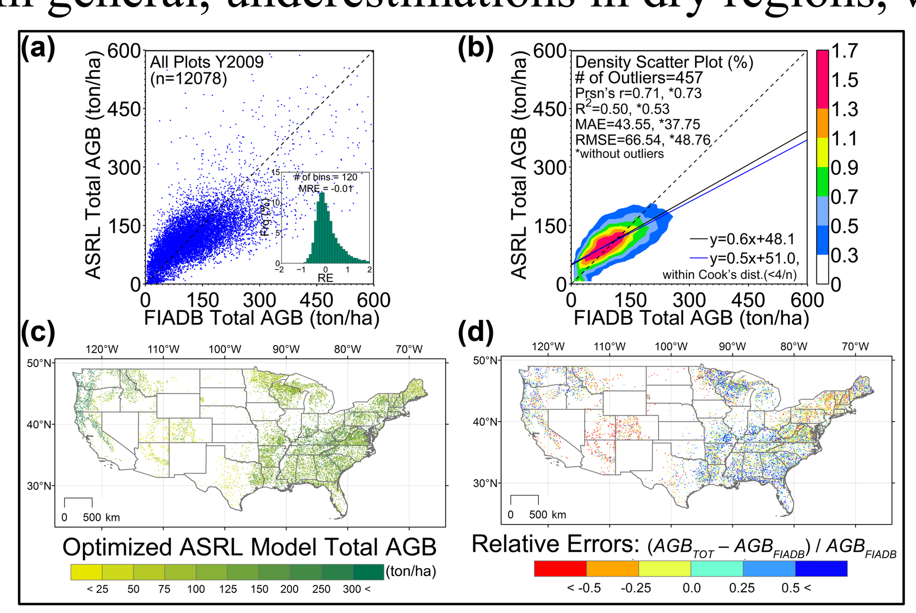


Fig 5. Optimized ASRL AGB (Y2009). (a) Overall agreement with FIA AGB. (b) Density scatter plot. (c) Spatial distribution. (d) Relative errors.

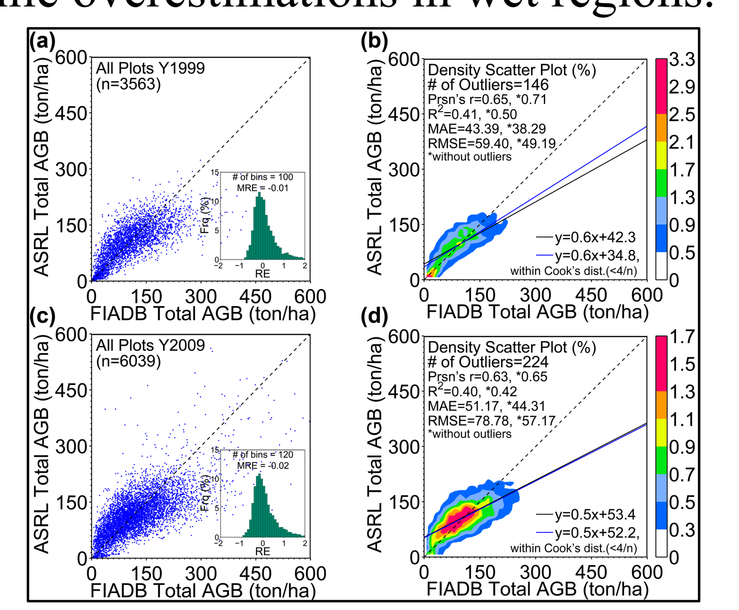
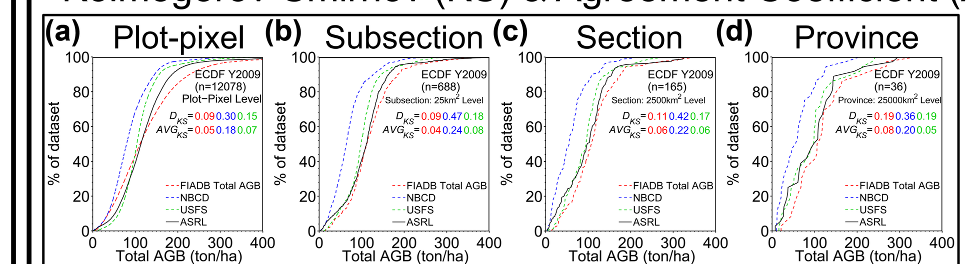


Fig 6. Two-fold cross validations for (a,b) Y1999 & (c,d) Y2009. Randomly divided training & test sets

VI. Intercomparisons of Modeled AGBs

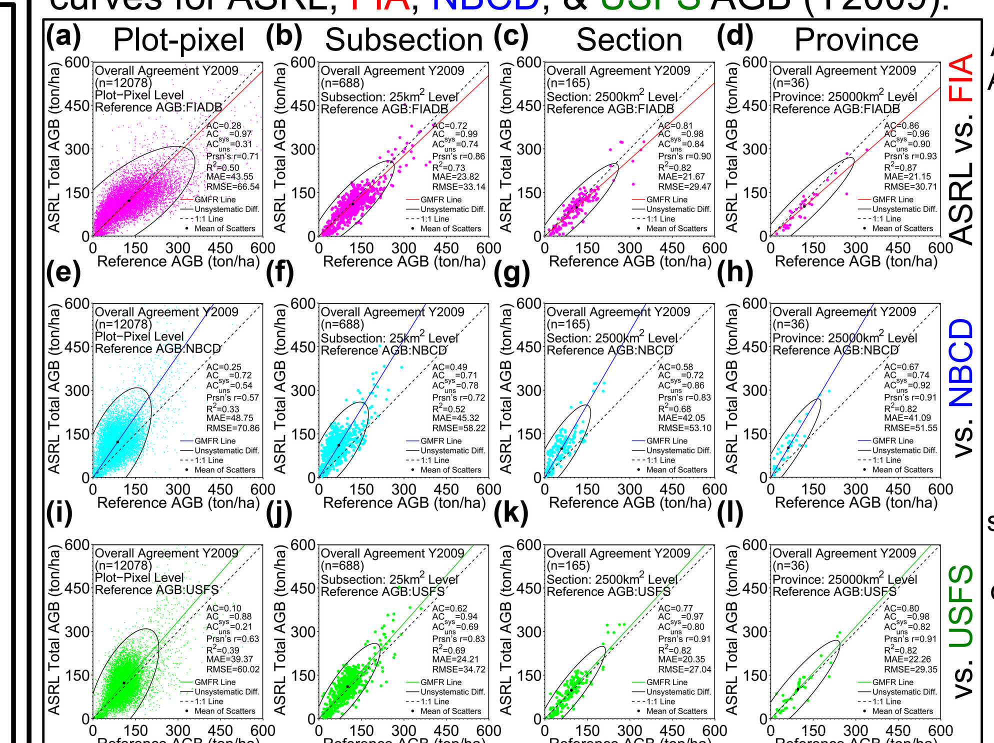
- Four standard comparisons[6] across spatial scales: (a) Data distribution, (b) Overall agreement, (c) Local mean, & (d) Variability in optimized ASRL & reference AGBs;
- ASRL vs. FIA generally showed best correlations & spatial similarity throughout all scales;

*Kolmogorov-Smirnov (KS) & Agreement Coefficient (AC) values



D_{KS} & AVG_{KS} < 0.20 for ASRL vs FIA (KS values close to zero represent a better agreement)

Fig 7. Empirical Cumulative Distribution Function curves for ASRL, FIA, NBCD, & USFS AGB (Y2009).



AC_{sys} > 0.96 ASRL vs FIA (AC values close to 1.0 represent a better agreement)

95% confidence ellipses show the un-systematic concurrence (also AC_{uns})

Fig 8. Overall agreement (Geometric Mean Function Relationship) of ASRL vs. FIA, NBCD, & USFS AGB.

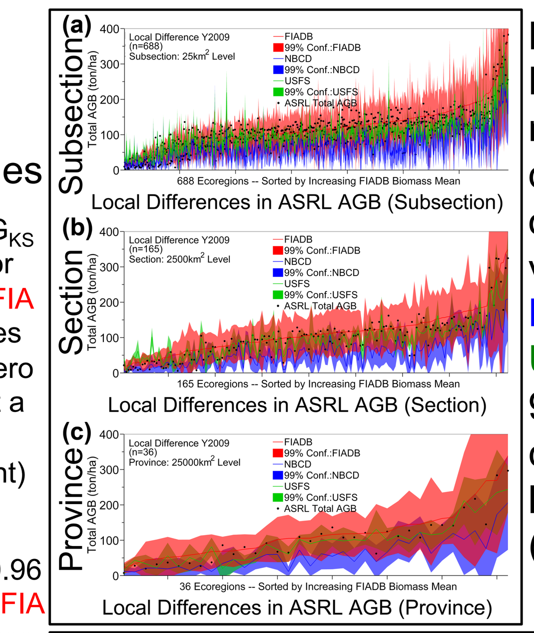


Fig 9. Local mean difference of ASRL vs. FIA, NBCD, & USFS with 99% confidence level (Y2009).

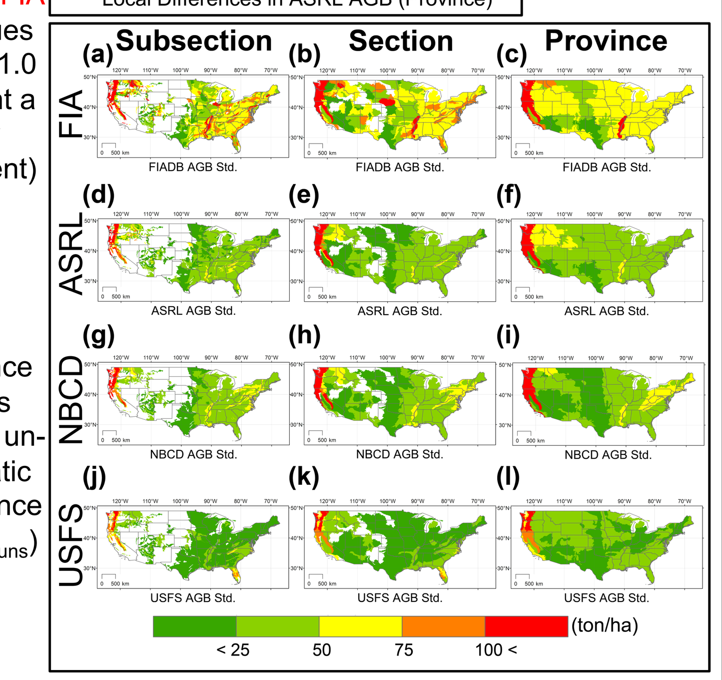


Fig 10. Local standard deviations in ASRL & reference AGBs (Y2009).

VII. Uncertainty Quantification

⦿ Error propagation for independent sources: $AGB_{TOT} = f(\rho, P_{inc}^{\psi}, A_e^{\psi})$.
- $\boldsymbol{U(p) = \{[\Delta\rho(p)/\rho(p)]^2 + [\psi\Delta P_{inc}(p)/P_{inc}(p)]^2 + [\psi S_{Ae}]^2\}^{1/2}}$; here, p = individual sites;

(a) spatial mismatches for FIA plots & PRISM pixels;
(b) heterogeneity of species composition;
(c) bias (0–80%) in effective root area (S_{Ae});
- Random errors (data quality) not considered;
- Source (a) & (b) only ≤ 10% of uncertainty;

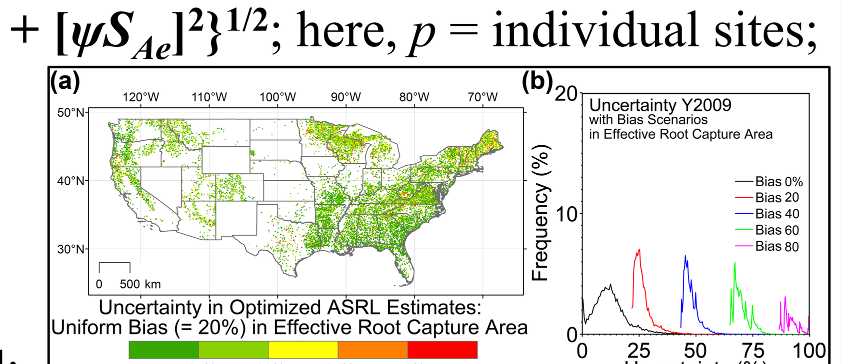


Fig 11. Quantified uncertainty (Y2009). (a) e.g., bias (20%) in S_{Ae}. (b) Five scenarios.

VIII. Future Improvements

⦿ **Spatially contiguous maps** of total forest AGB after alleviating limitations.
(a) Additional geospatial predictors may be needed – e.g., evaporative fluxes, soil nutrients & properties;
(b) Improved calibration of basal metabolic constants and exponents is required;
(c) Explicit accounting of forest stand age structure is necessary;

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Acknowledgements

This work was partially supported by the **Fulbright Graduate Scholarship** and by the NASA Headquarters under the **NASA Earth and Space Science Fellowship** Program – Grant "NNX13AP55H"